DFT: Learning

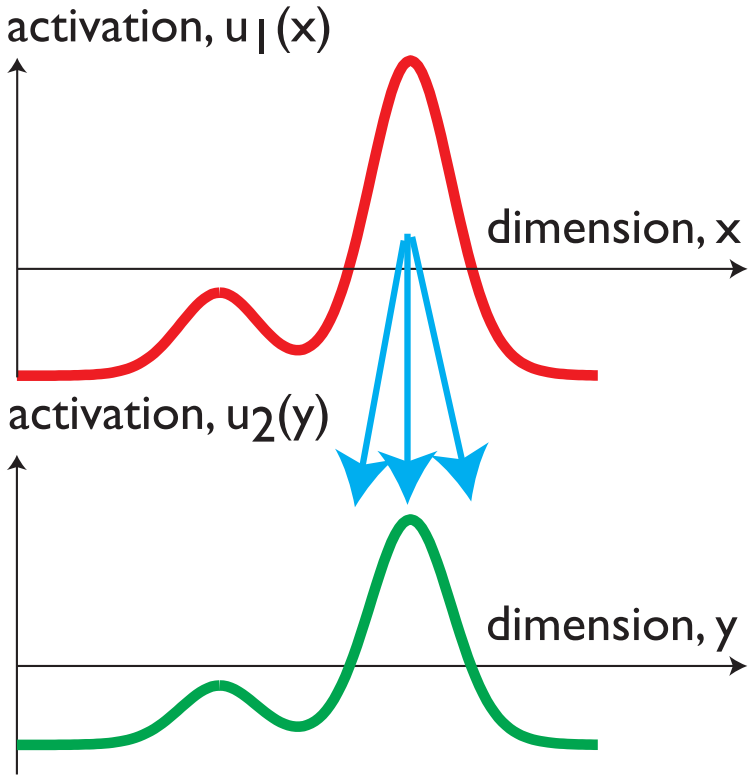
Gregor Schöner
Institute for Neural Computation (INI)
dynamicfieldtheory.org

Patterns of forward connectivity give meaning to neural fields

- how do these patterns arise?
  - morphogenesis… modeled by fixed connectivity
  - learning…

Hebbian learning

- Hebbian learning of projections
  - among fields
  - forward from sensory input to fields
- interaction leads to localized rather than distributed representations (SOM)

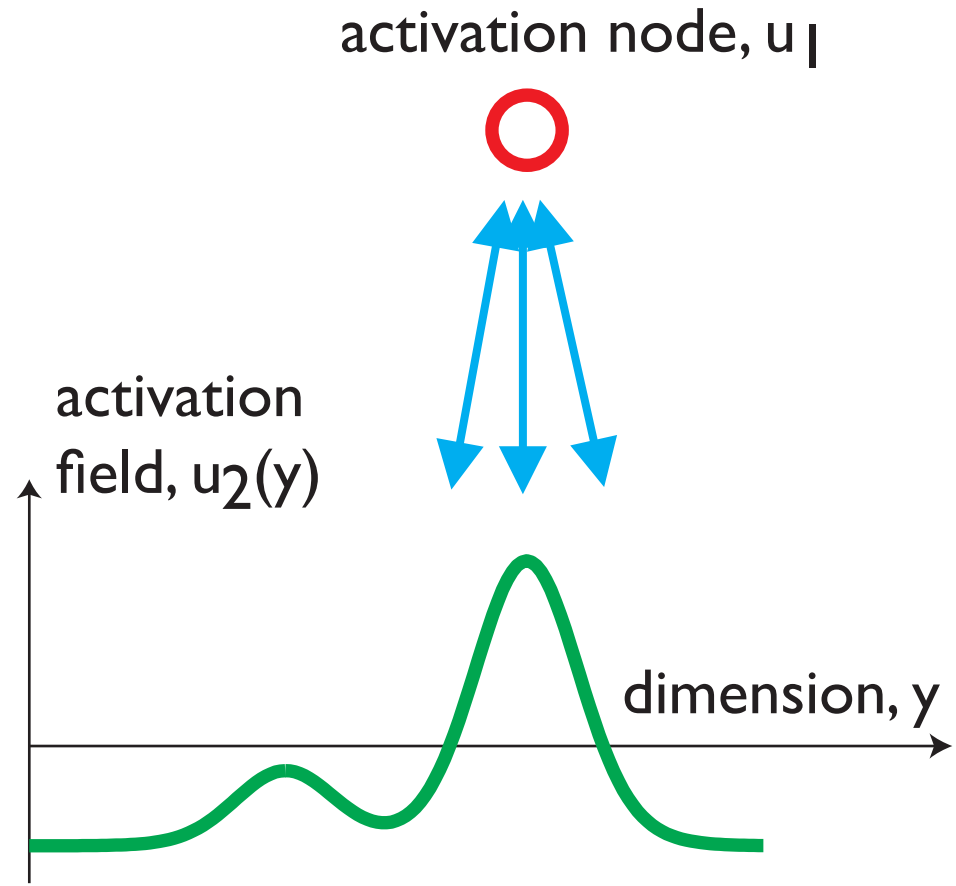


$$\tau \dot{W}(x, y, t) = \epsilon(t)\Big(- W(x, y, t) + f(u_1(x, t)) \times f(u_2(y, t))\Big)$$

[Sandamirskaya, *Frontiers Neurosci* 2014]

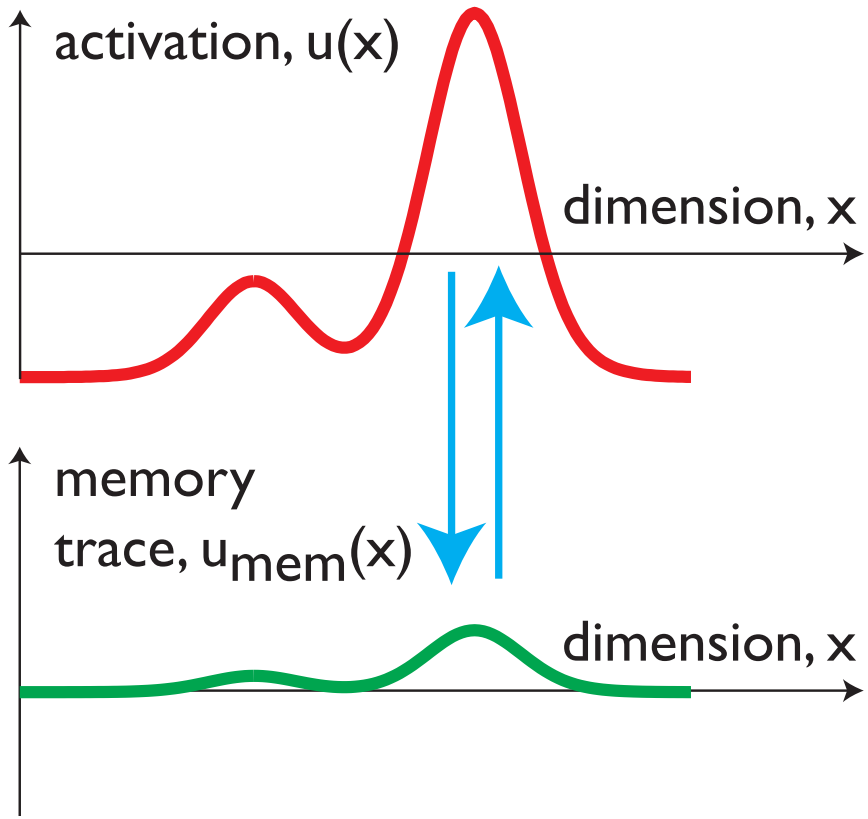
Hebbian learning

- learning reciprocal connections between zero-dimensional nodes and fields
- => grounded concepts
- analogous to the output layer of DNN
- => ensembles of such nodes coupled inhibitorily form the basis for conceptual thinking…



The memory trace

- facilitatory trace of patterns of activation
- in excitatory field: leads to sensitization
- in inhibitory field: leads to habituation

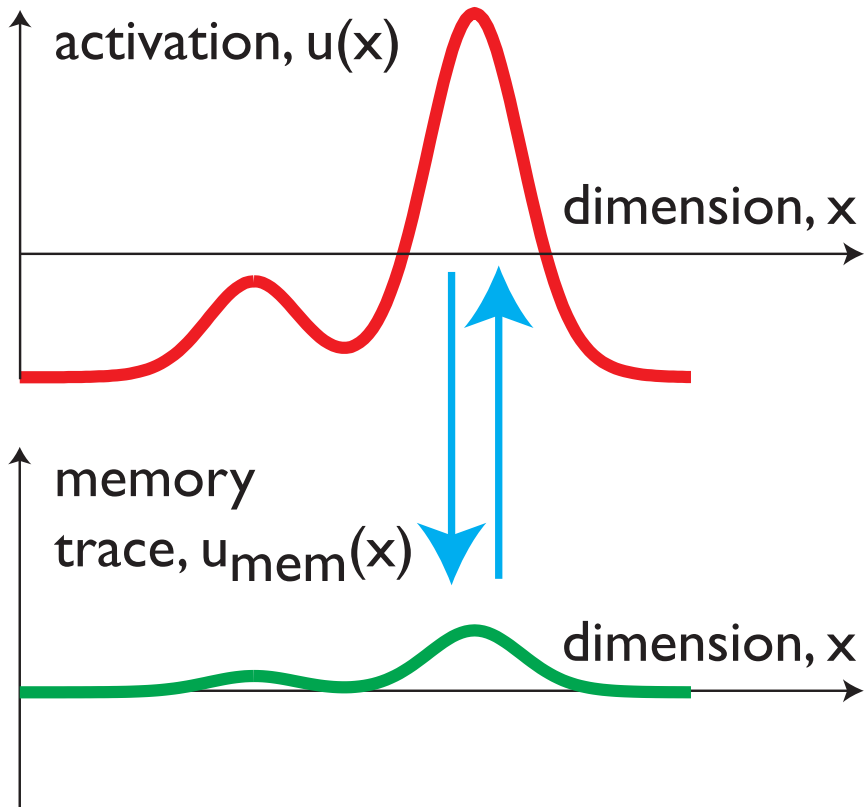


The memory trace

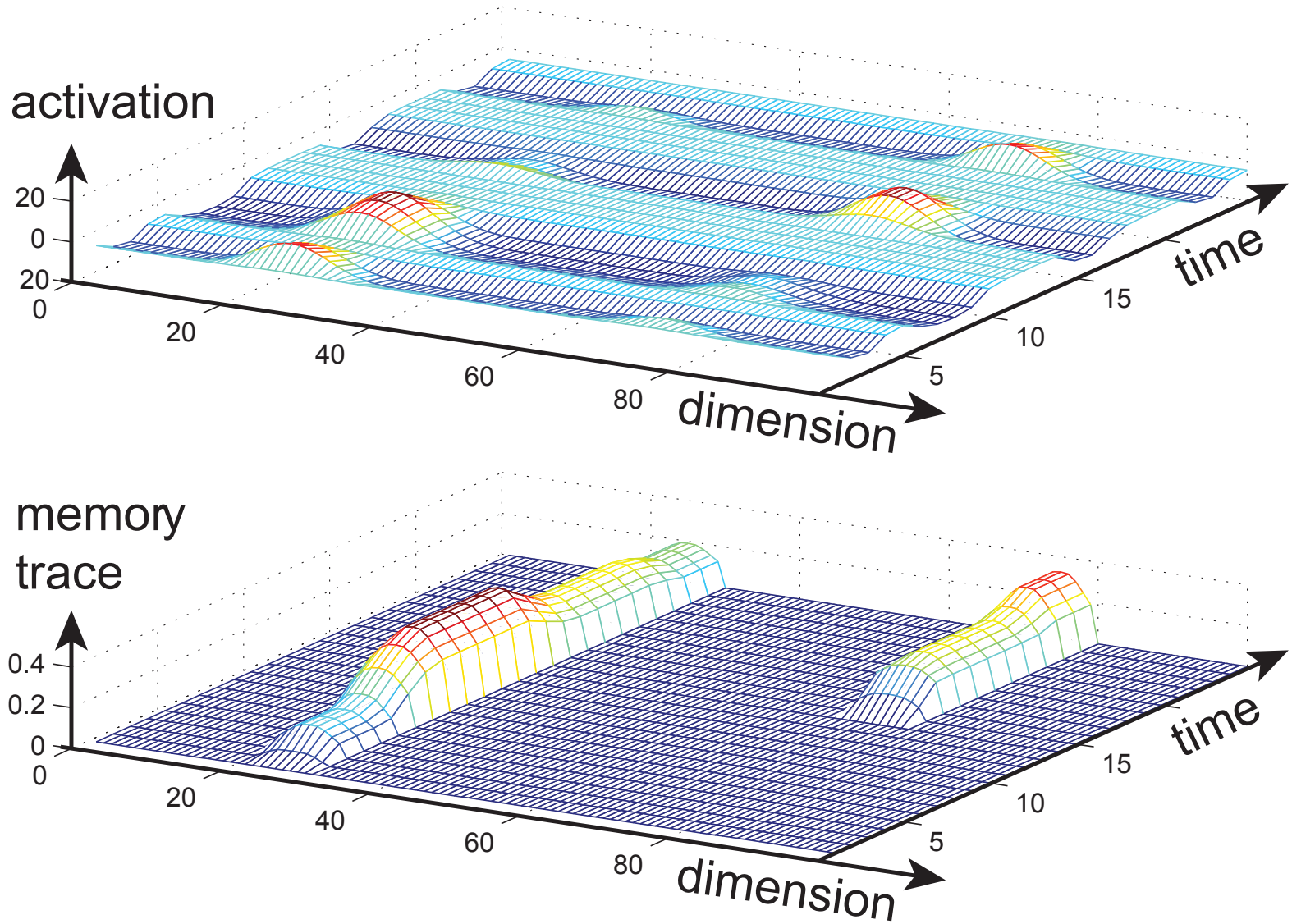
$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int dx' w(x-x')\ \sigma(u(x',t)) + u_{\text{mem}}$$

$$\tau_{\text{mem}} \dot{u}_{\text{mem}}(x,t) = -u_{\text{mem}}(x,t) + \sigma(u(x,t))$$

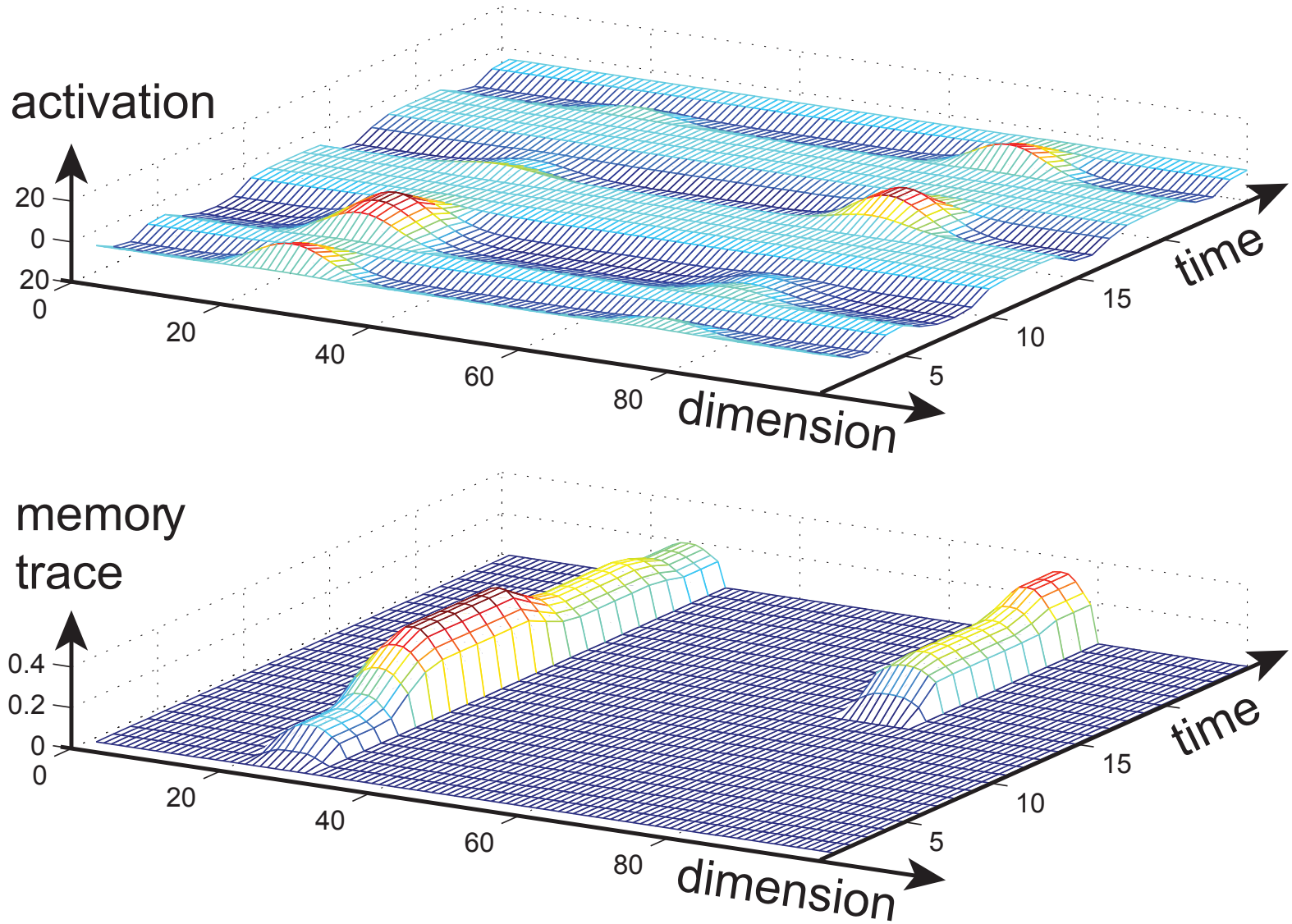
$$\tau_{\text{mem}} \dot{u}_{\text{mem}}(x,t) = 0 \quad \text{if} \int dx' \sigma(u(x',t)) \approx 0$$



=> the memory trace reflects the history of detection decisions

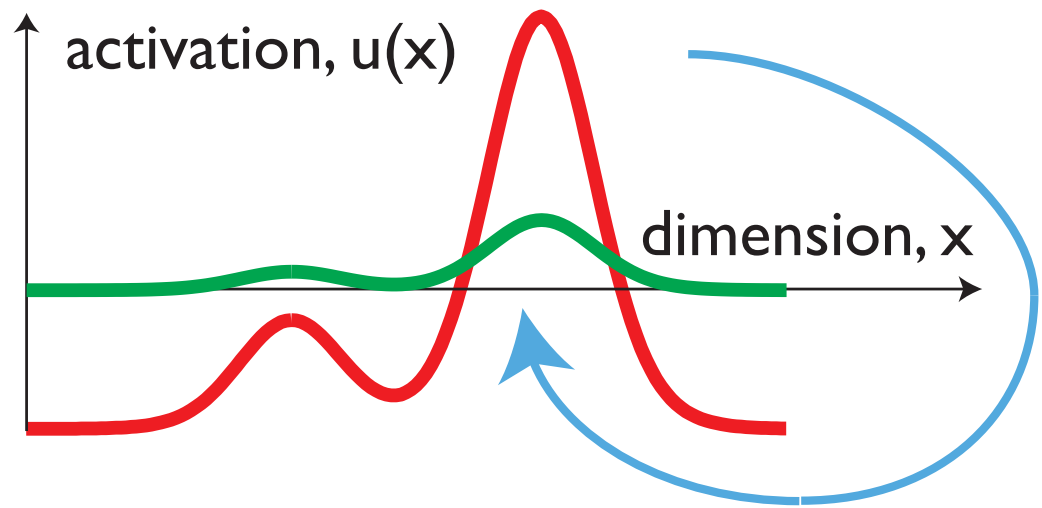


The memory trace suffers from interference



Memory trace ~ first-order Hebbian learning

- increases local resting level at activated locations
- ~ the bias input in NN
- boost-driven detection instability amplifies small bias => important role in DFT



The memory trace is functionally different from conventional Hebbian learning

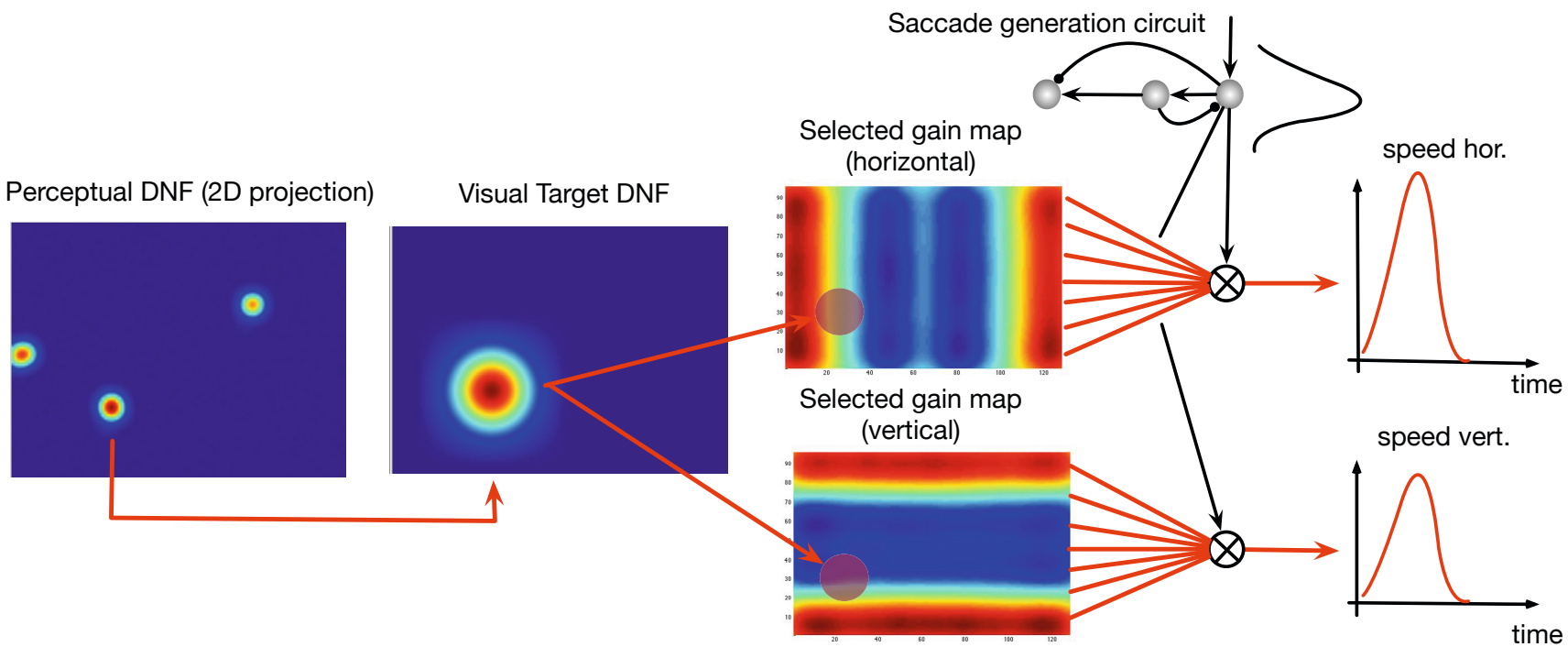
- the memory trace enables the re-activation of a past pattern of activation even when the input that caused the past pattern of activation is absent
- this is the basis for cued recall in DFT

Autonomous learning

- Learning from experience..
- .. which requires first.. experience!
- Hypothesis; this is what learning in humans and other animals entails!

Variants of autonomous learning: Adaptation

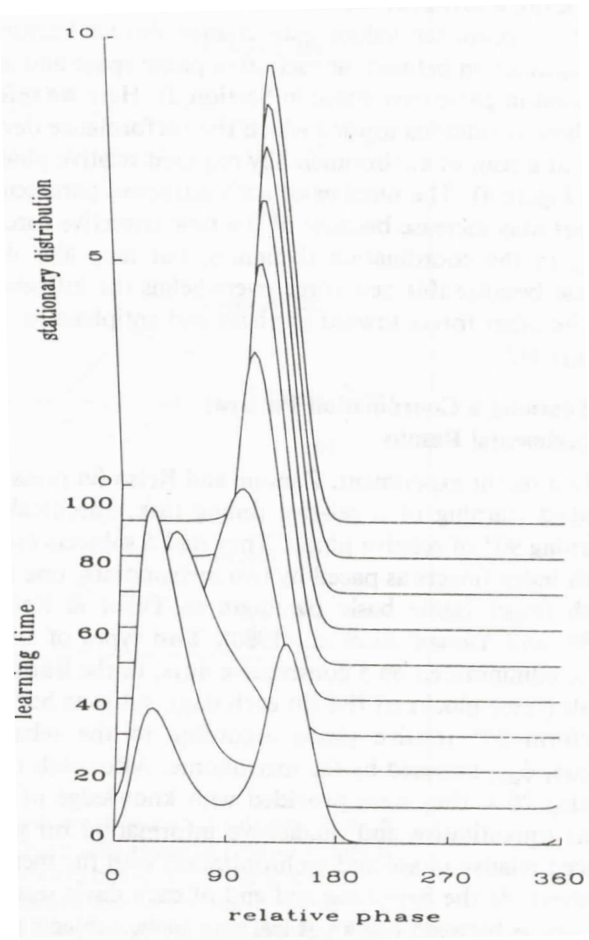
- Example: adjusting gain of saccadic eye movements… Sandamirskaya et al
- even this "simple" form of adaptation requires extensive processing infrastructure

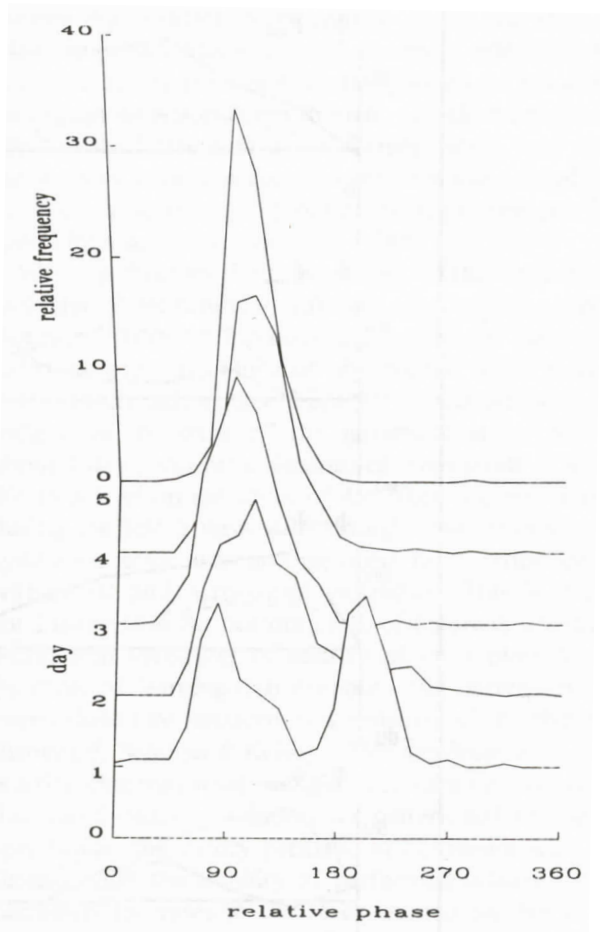


[Storck, Sandamirskaya, *LNCS* 2014]

Variants of autonomous learning: Skill

- Old work in movement coordination… suggests that learning is change of dynamics… stabilization of new patterns
- related work in multi-joint movement

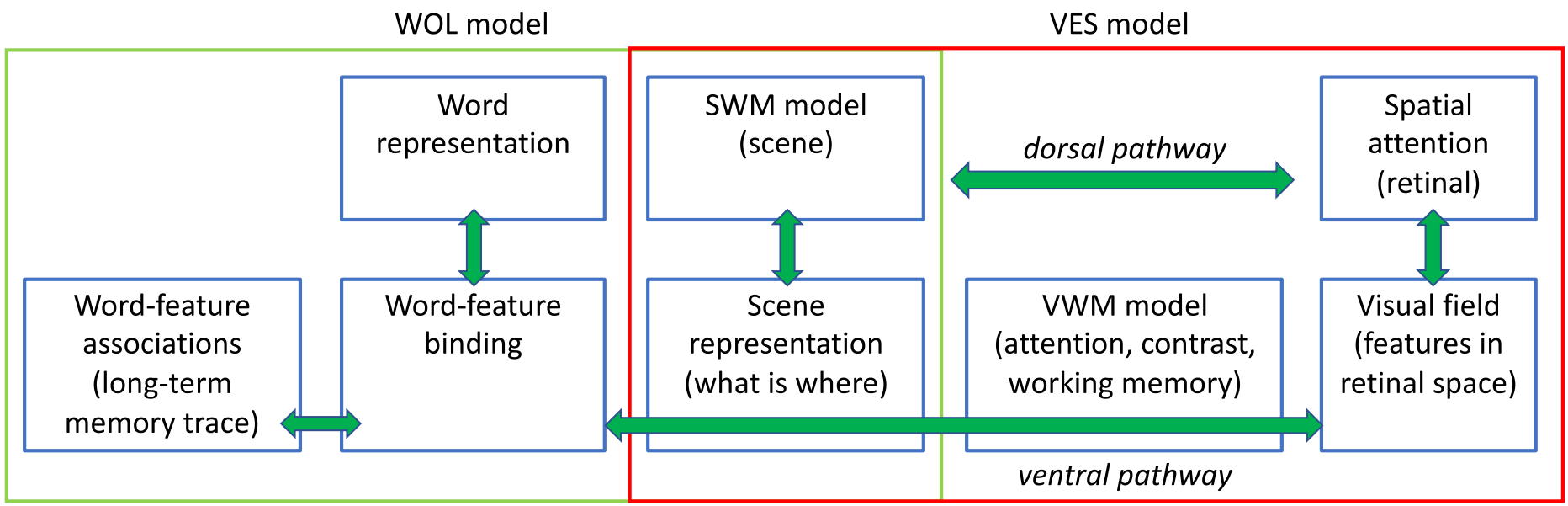




[Schöner, Zanone, Kelso, *JMB*, 1992\

Variants of autonomous learning: Words

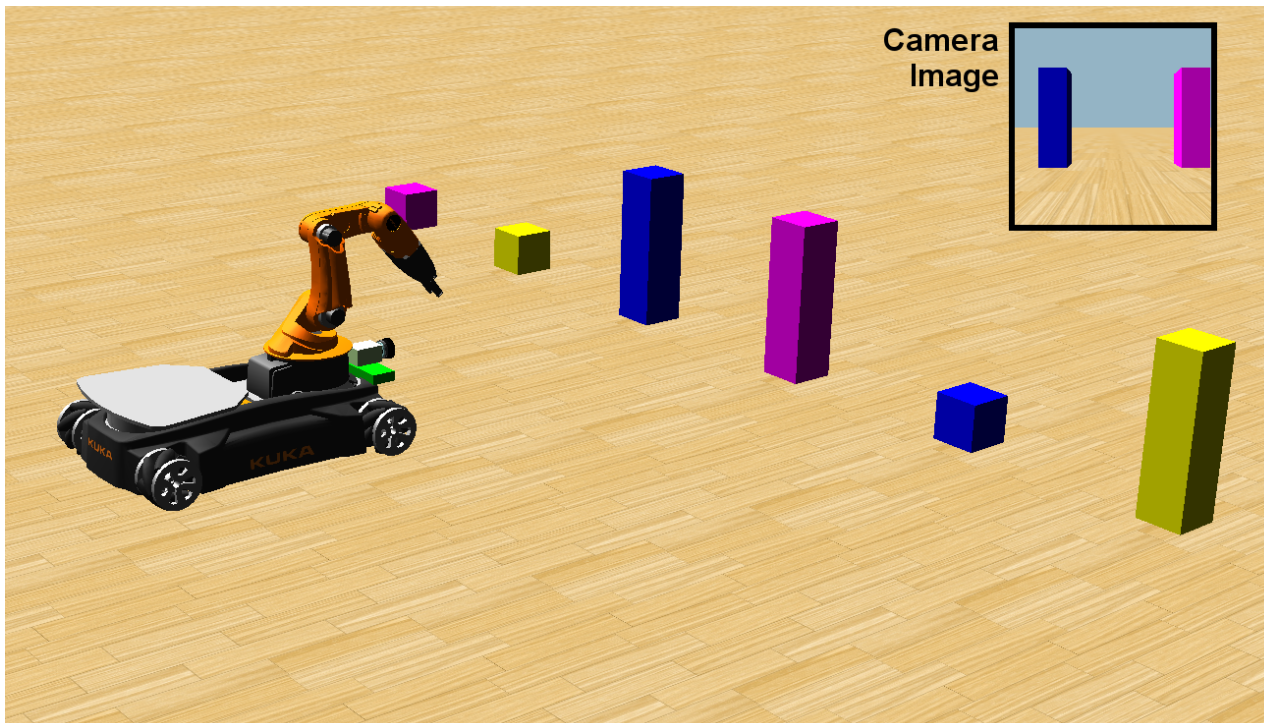
- linking word representations (nodes) to features of objects
- tracking word-feature binding across episodes of experiencing the word (cross-situational word learning)



[Bhat, Spencer, Samuelson, *Psych Rev* 2023]

Variants of autonomous learning: Contingencies

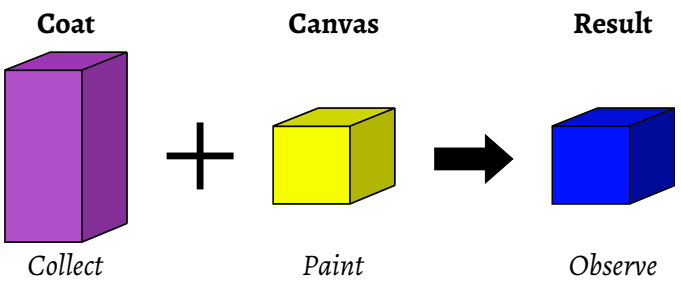
- learning regularities in the world (contingencies, rules) by acting on the world
- an important part of development
- DFT: an intentional agent acts on the word and gathers experience: later lecture

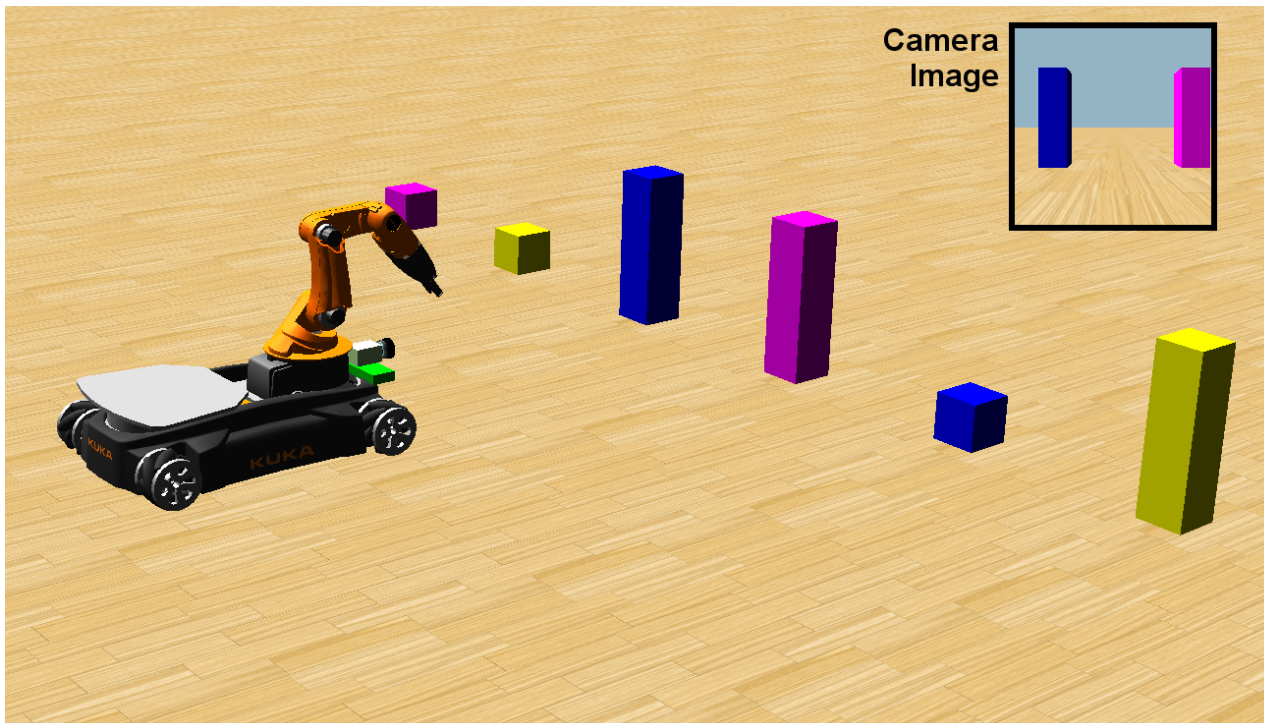


[Tekülve, Schöner, IEEE Trans Cog Dev Sys 2022;
Tekülve, Schöner Cog Science, in press (2024)]

Variants of autonomous learning: Contingencies

- learns color rules of painting from a single episode of this sequences of events:
- collects paint of a given color from a container (coat)
- paints a canvas container
- observes result color

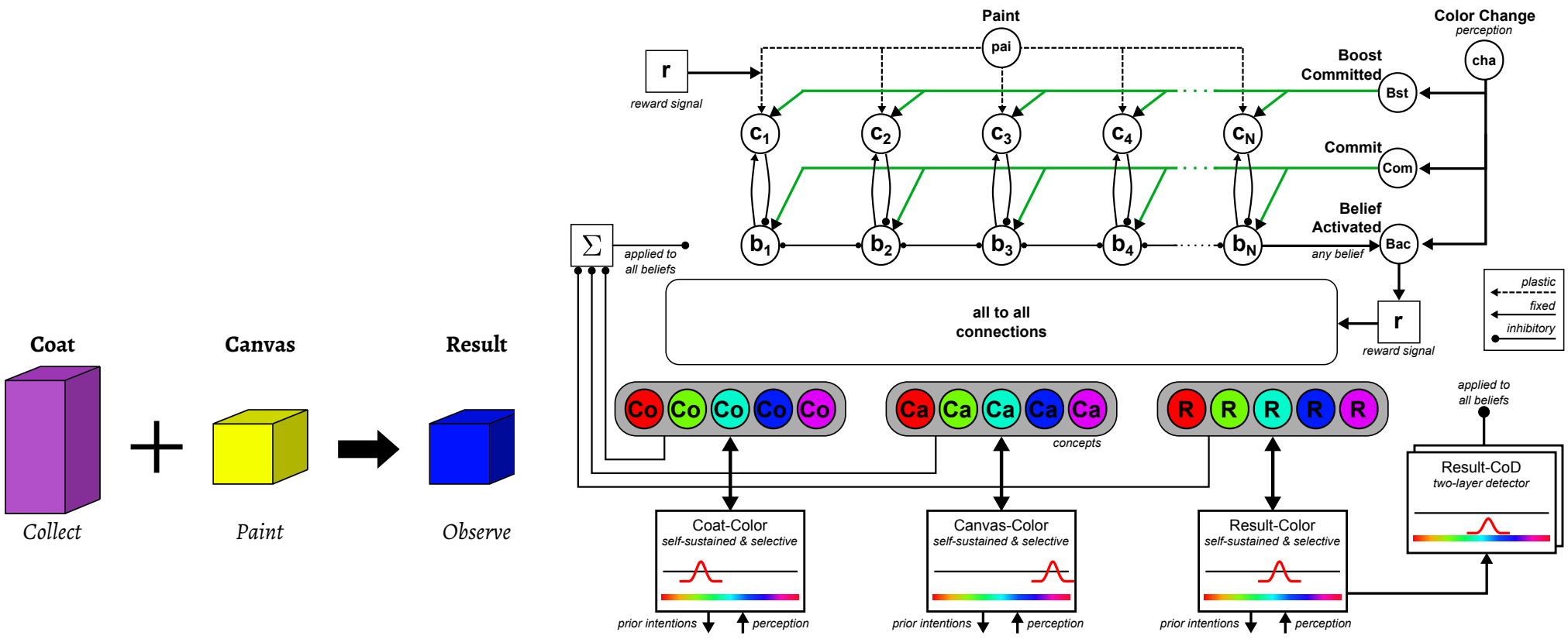




[Tekülve, Schöner, *IEEE Trans Cog Dev Sys* 2022;
Tekülve, Schöner *Cog Science* (2024)]

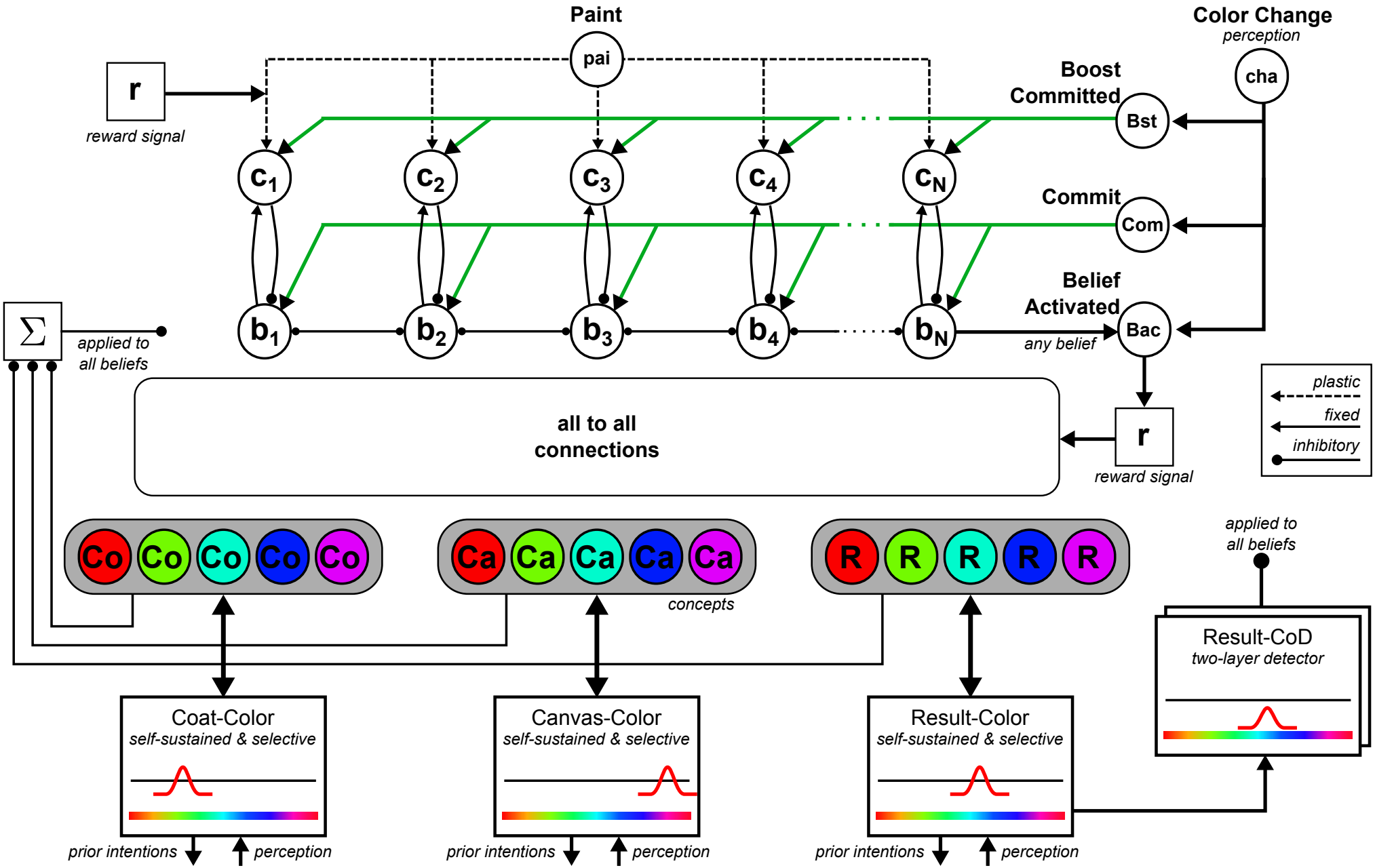
Variants of autonomous learning: Contingencies

- that learned contingency is represented as a "belief" in a network

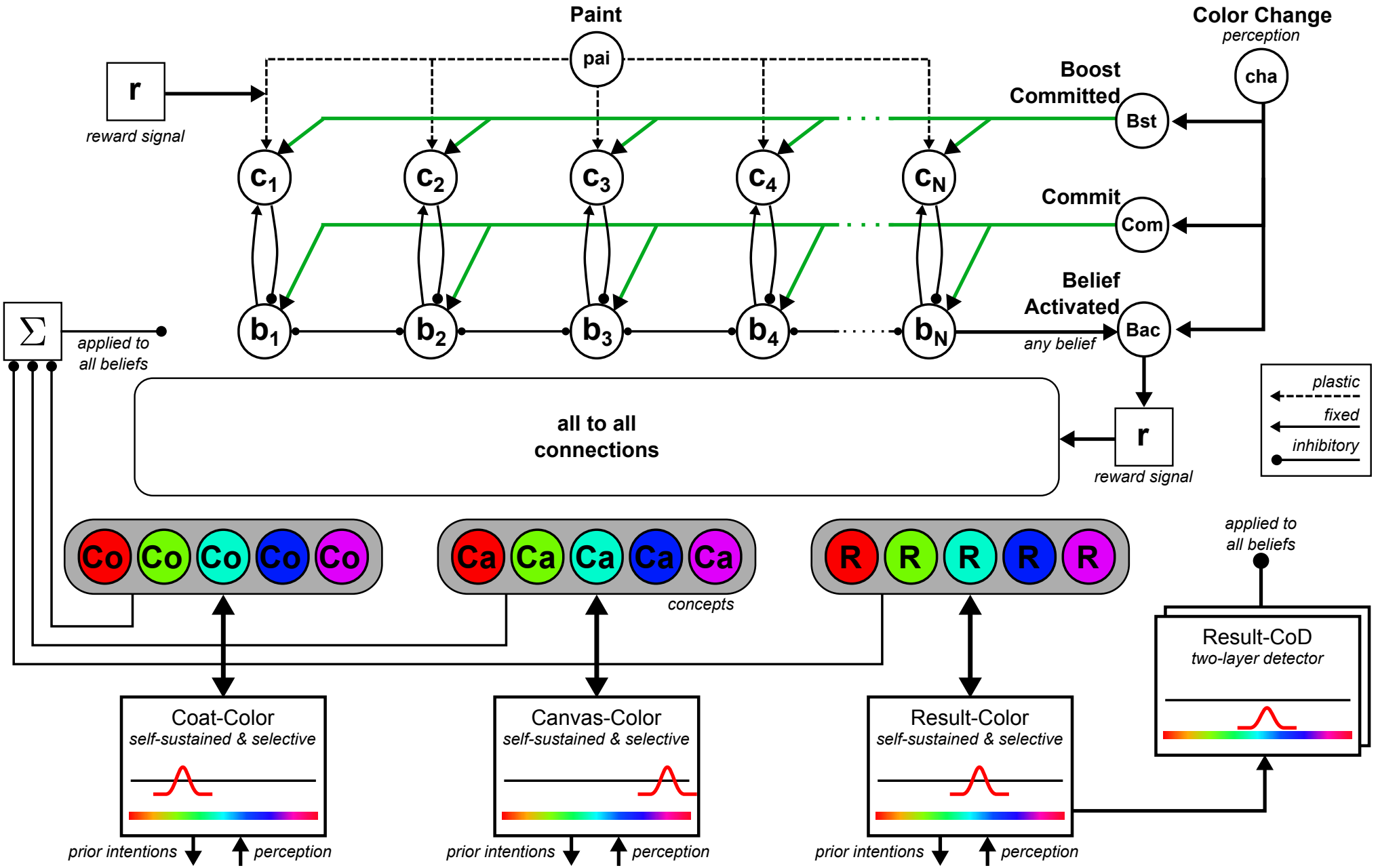


[Tekülve, Schöner, *IEEE Trans Cog Dev Sys* 2022;
Tekülve, Schöner *Cog Science* (2024)]

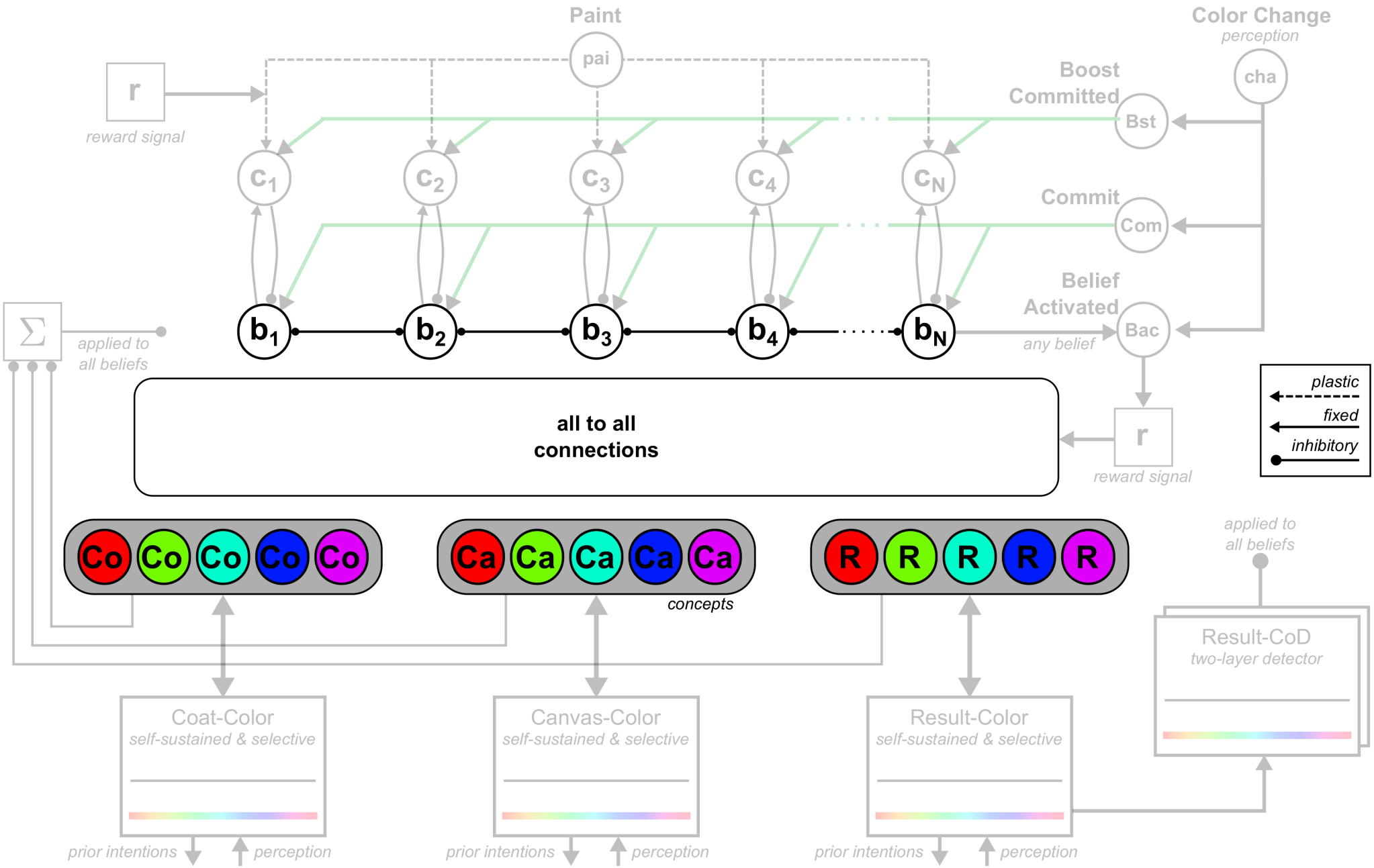
Belief network



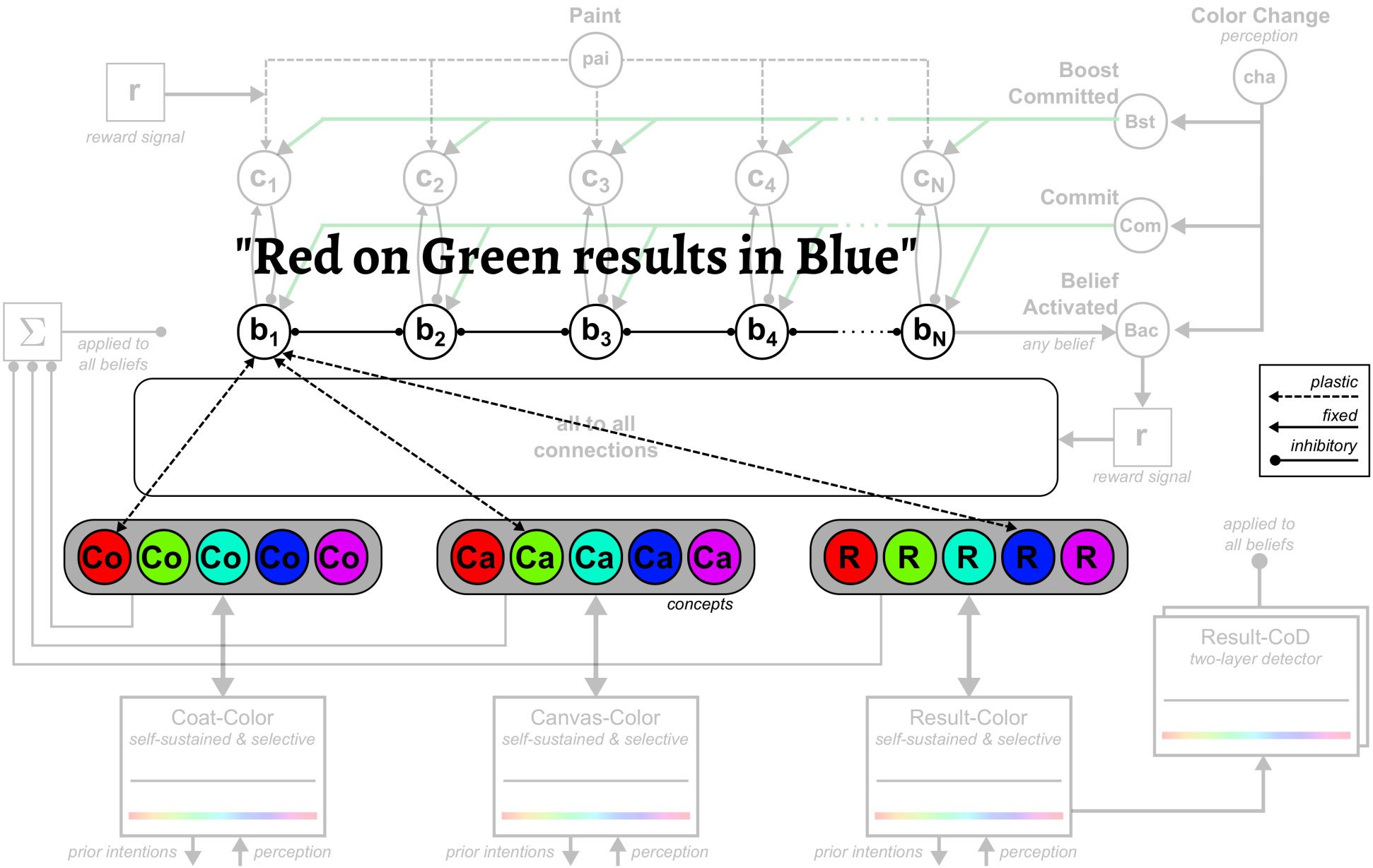
~Adaptive resonance ART Grossberg



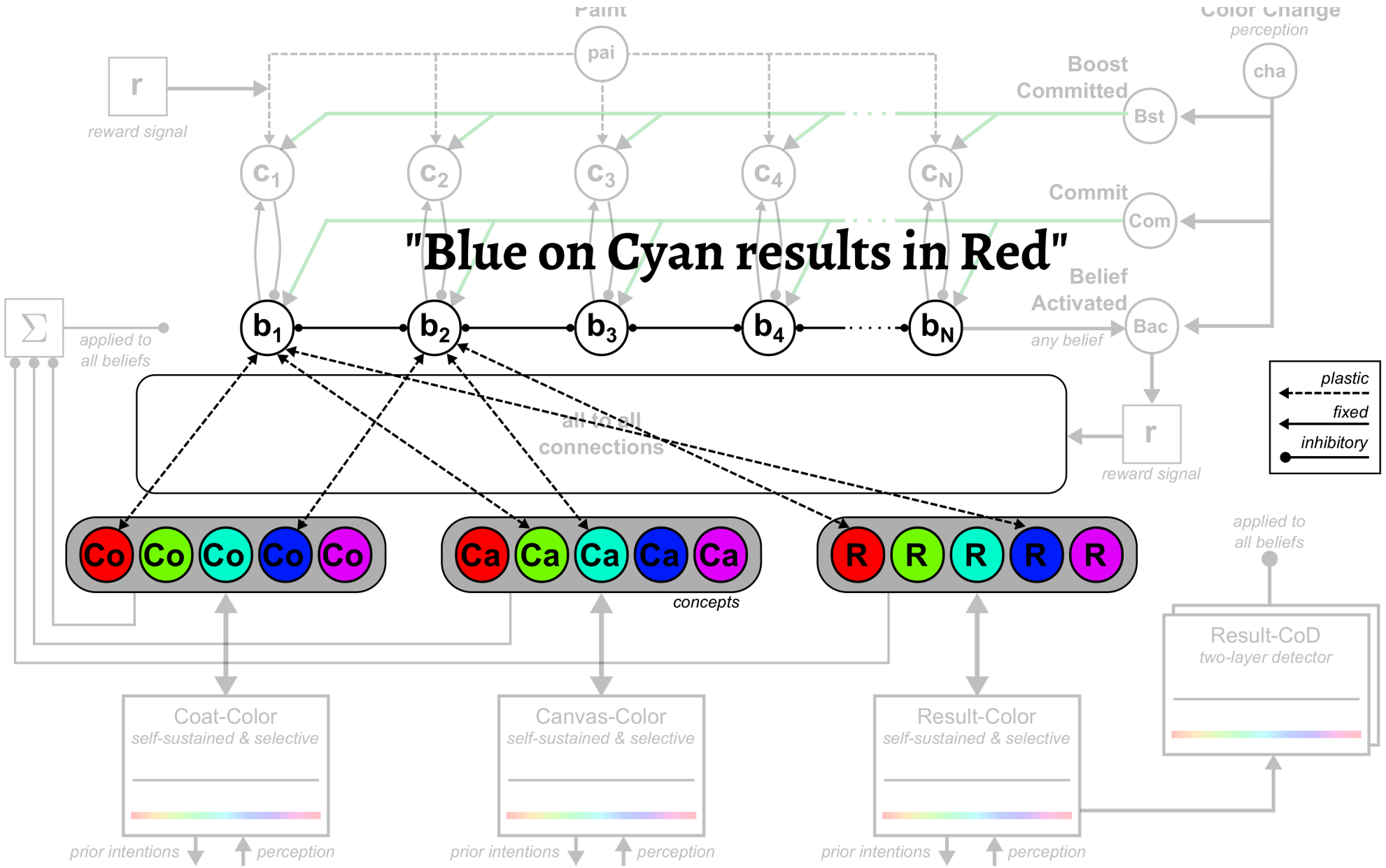
Belief and concept/role nodes



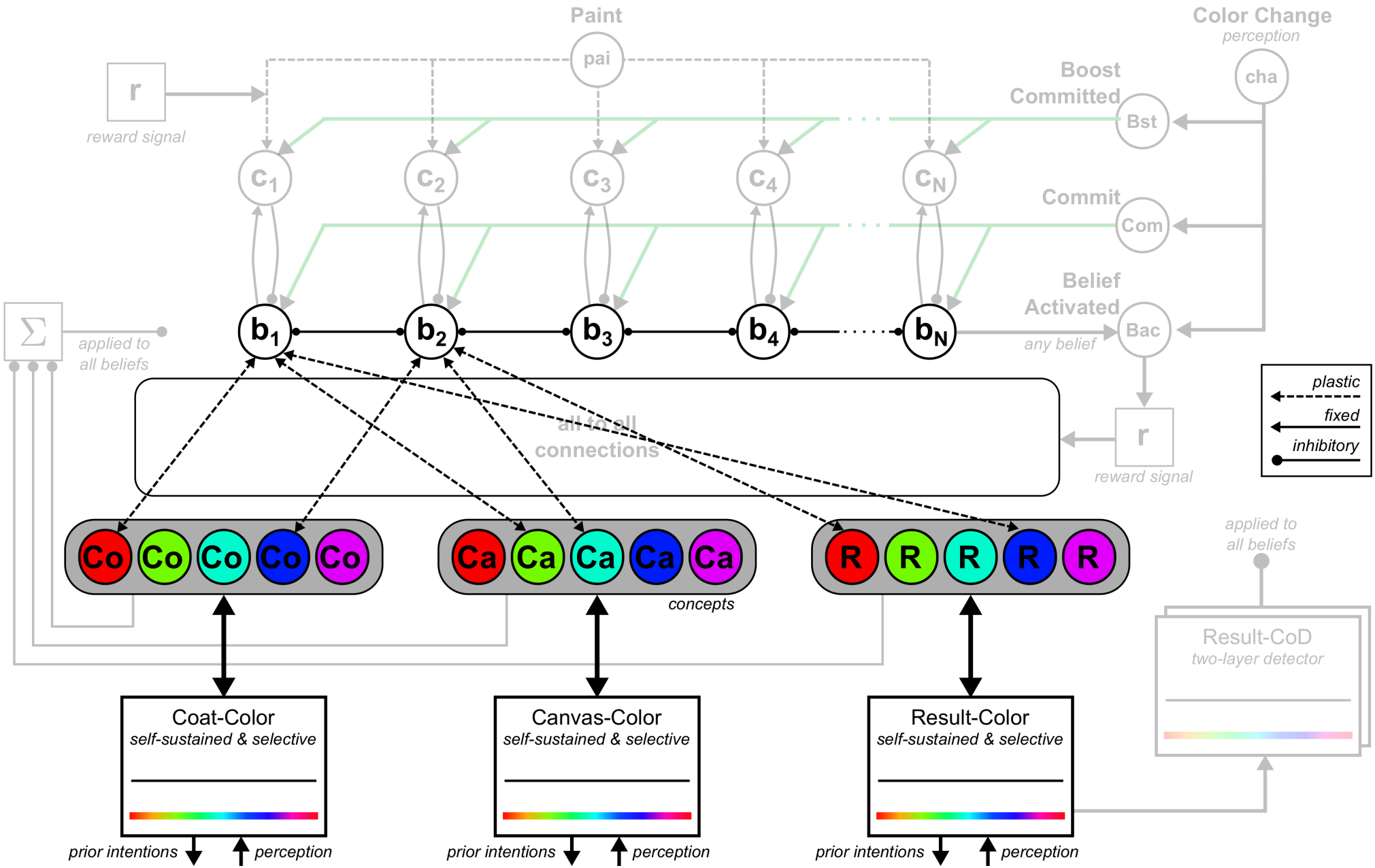
Representing a belief



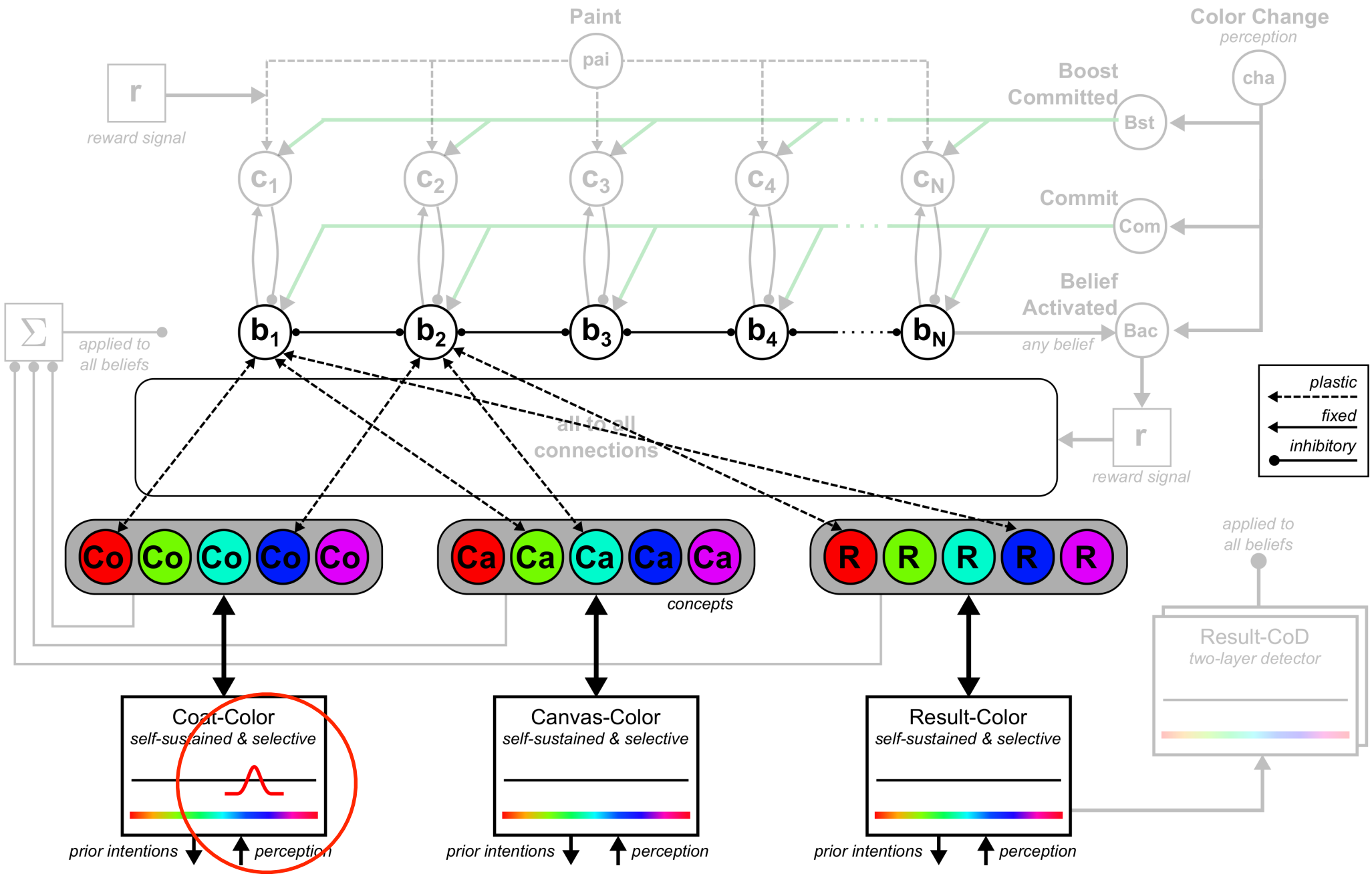
Representing a belief



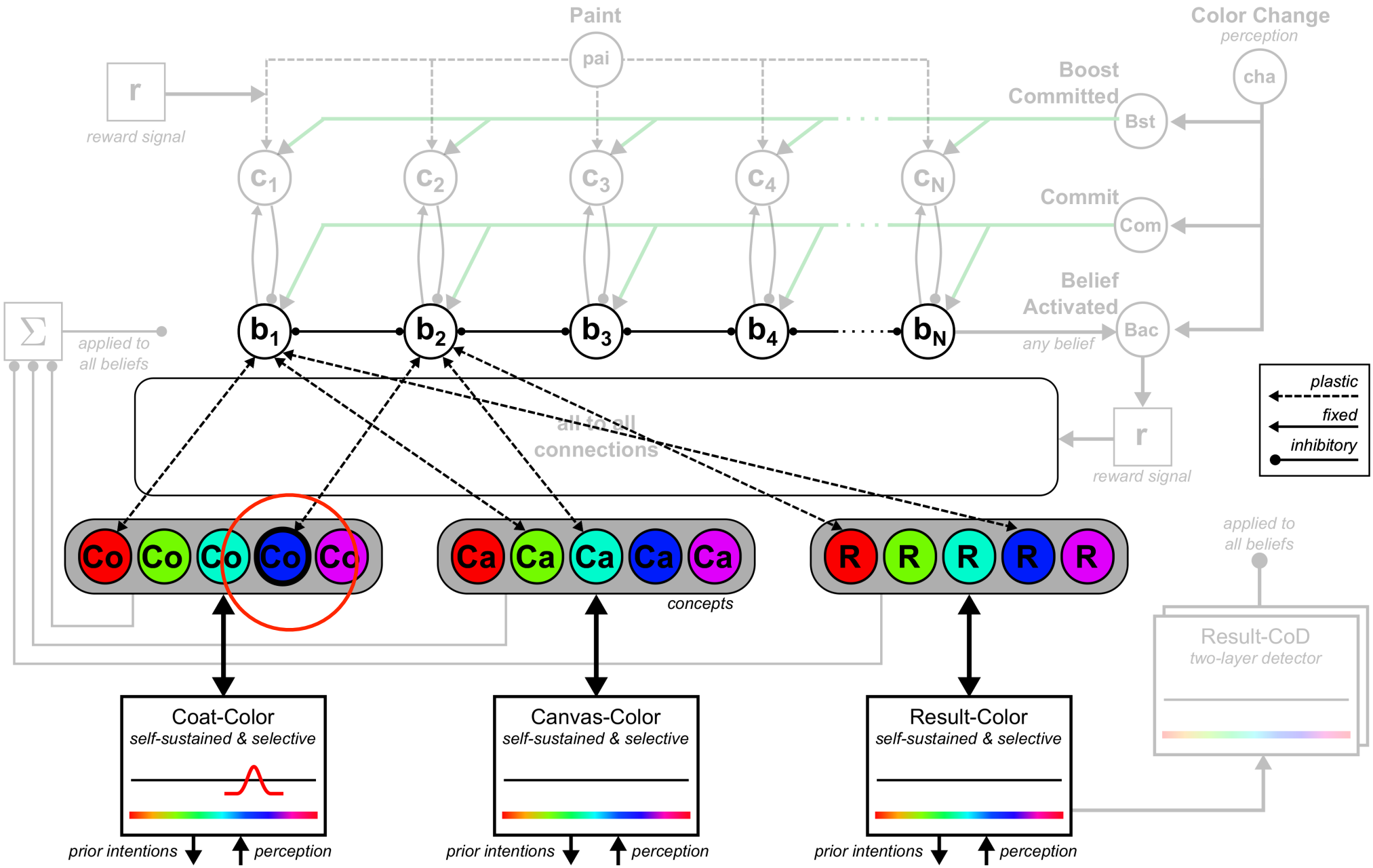
Grounding of the concept nodes



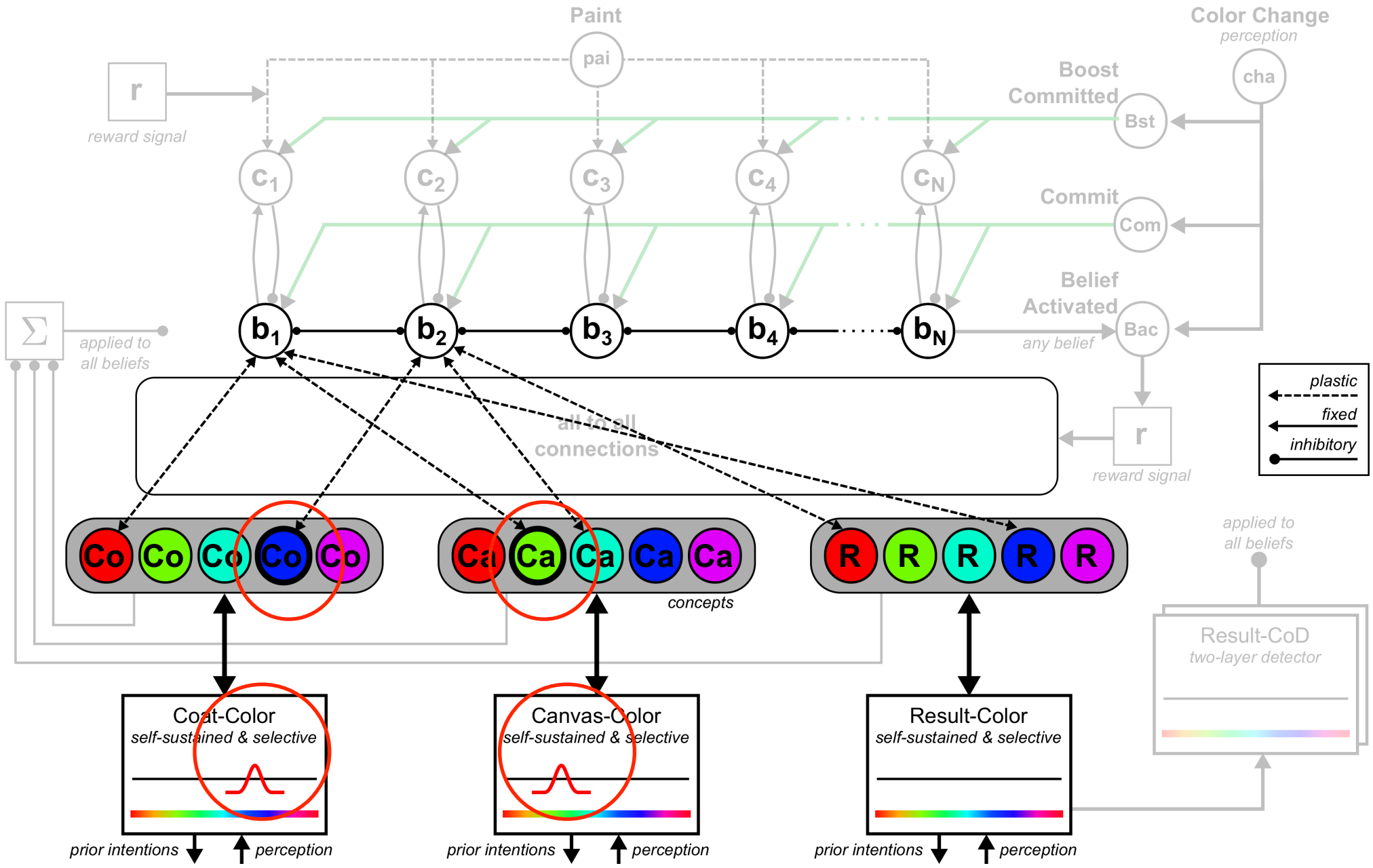
Coat color detected



Activates color/role concept node

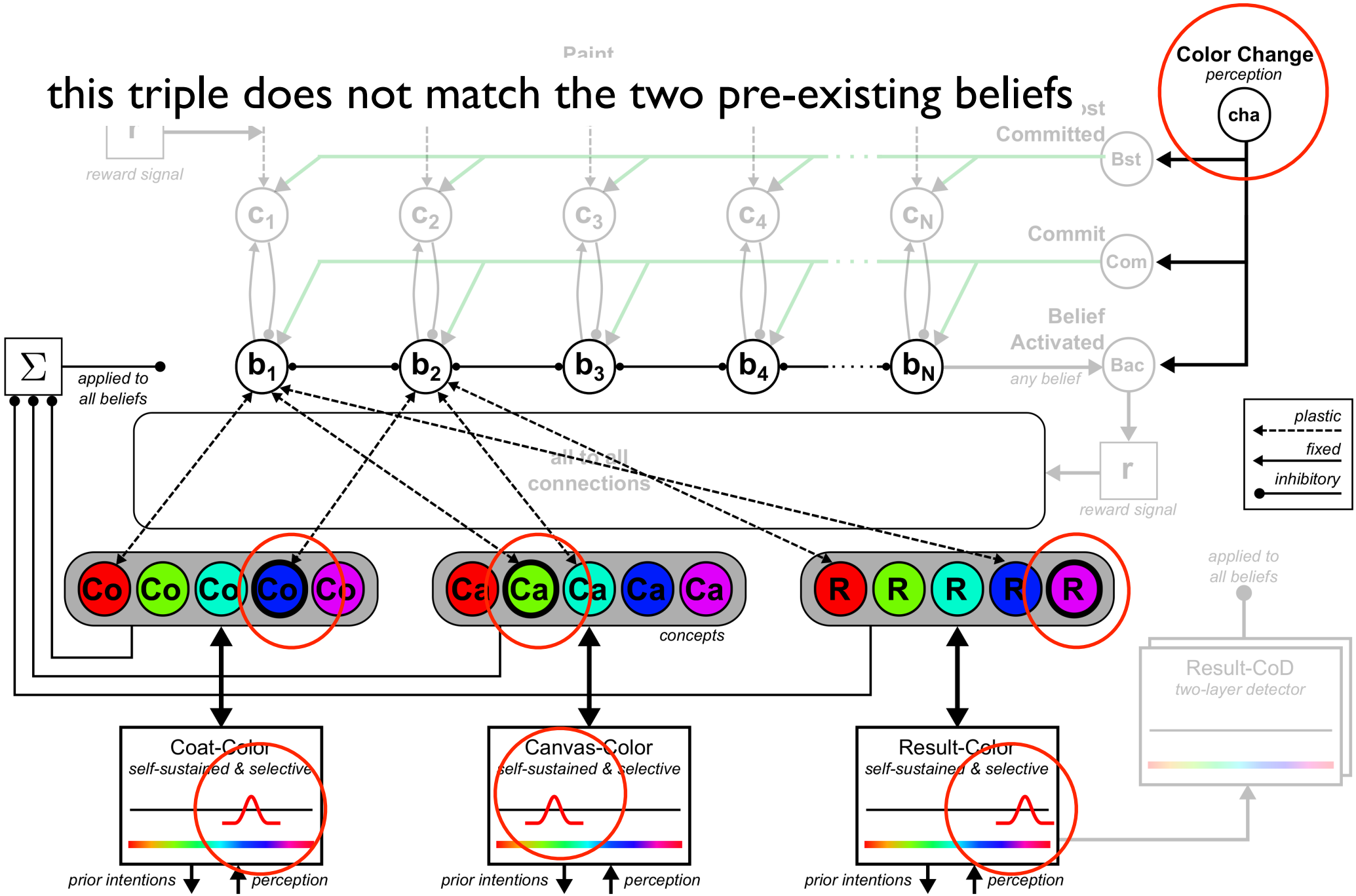


Coat and canvas color concepts activated

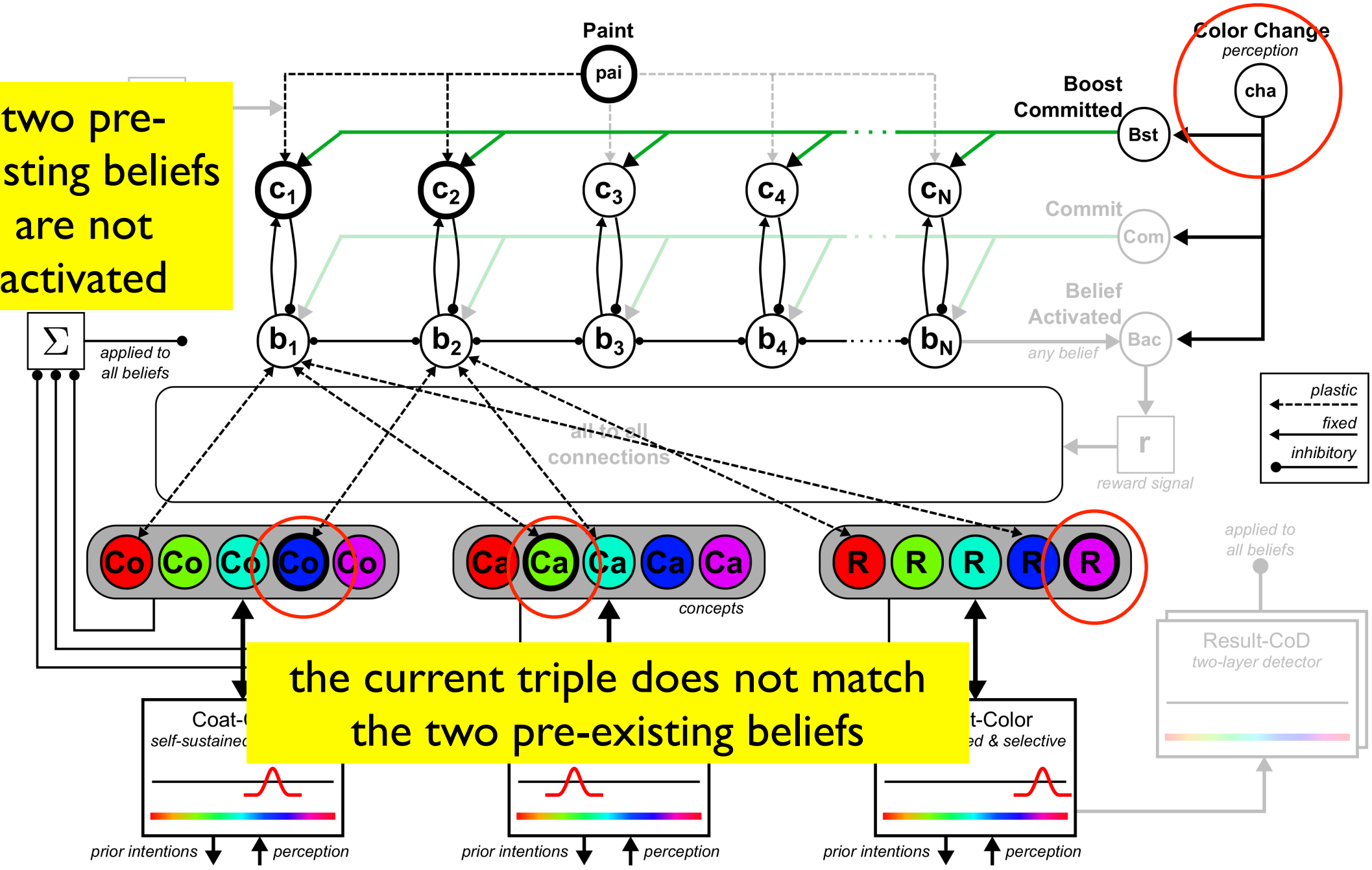


Result concept activated and change detected

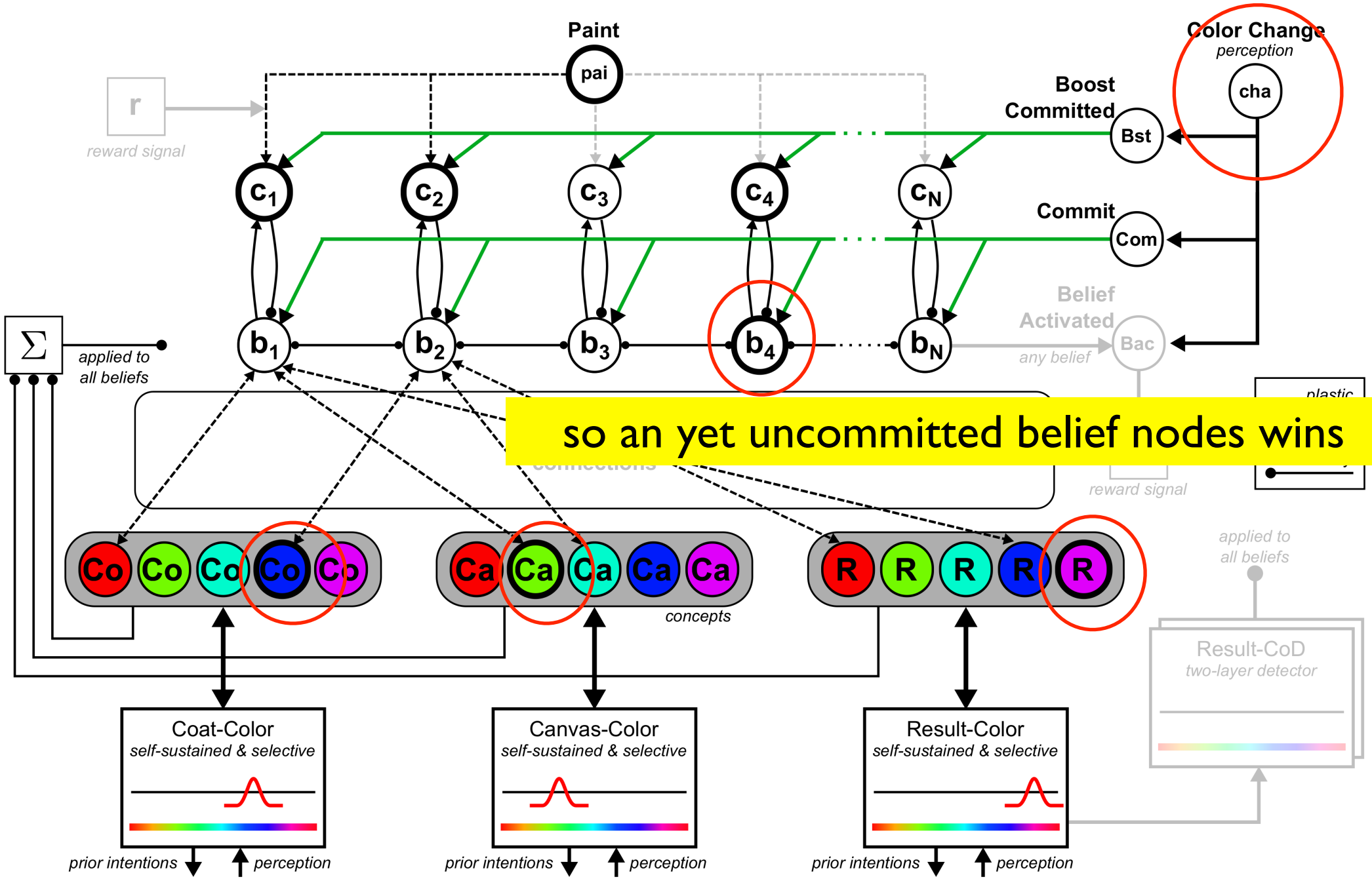
this triple does not match the two pre-existing beliefs



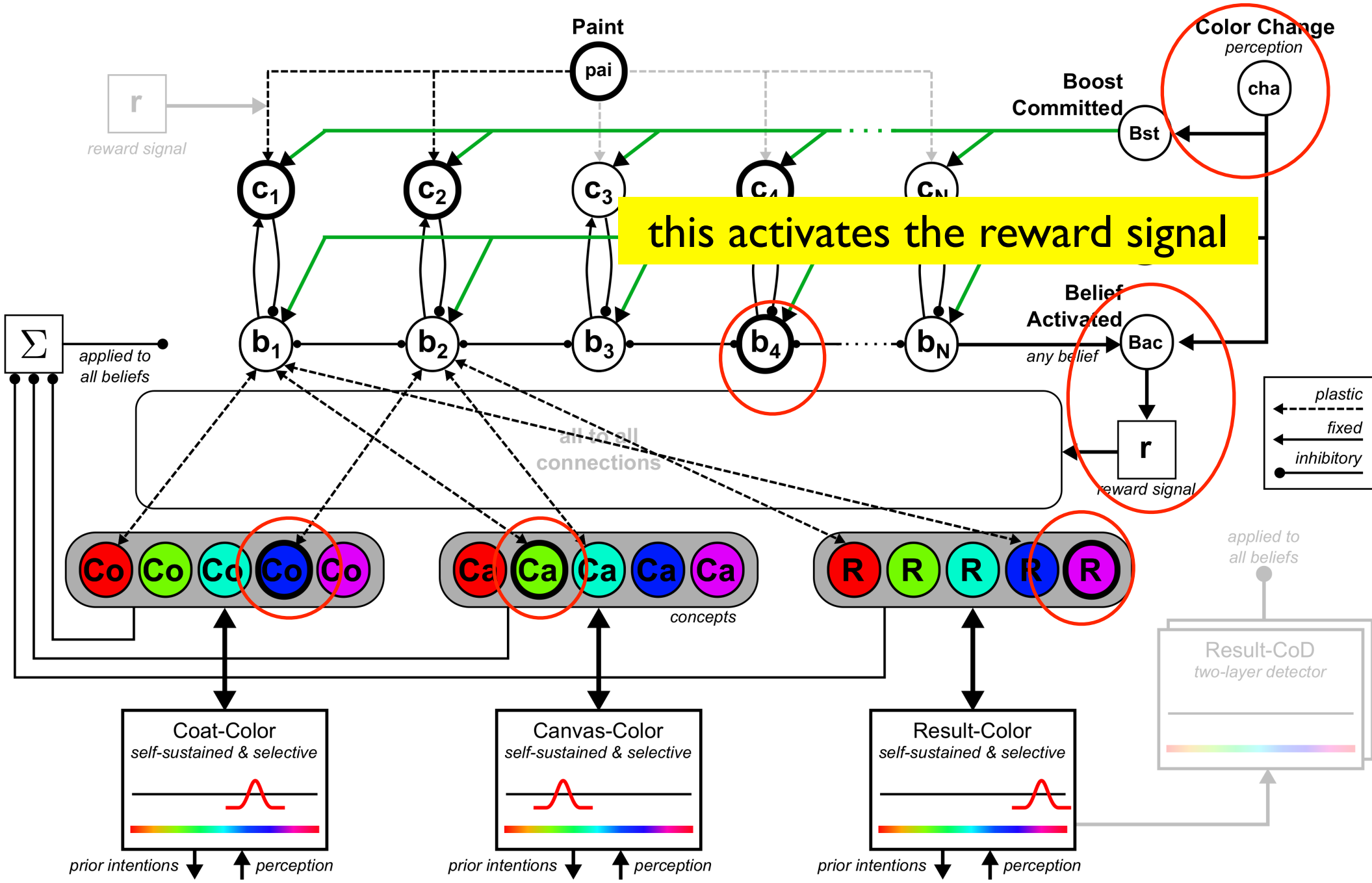
Commit nodes activated, task active



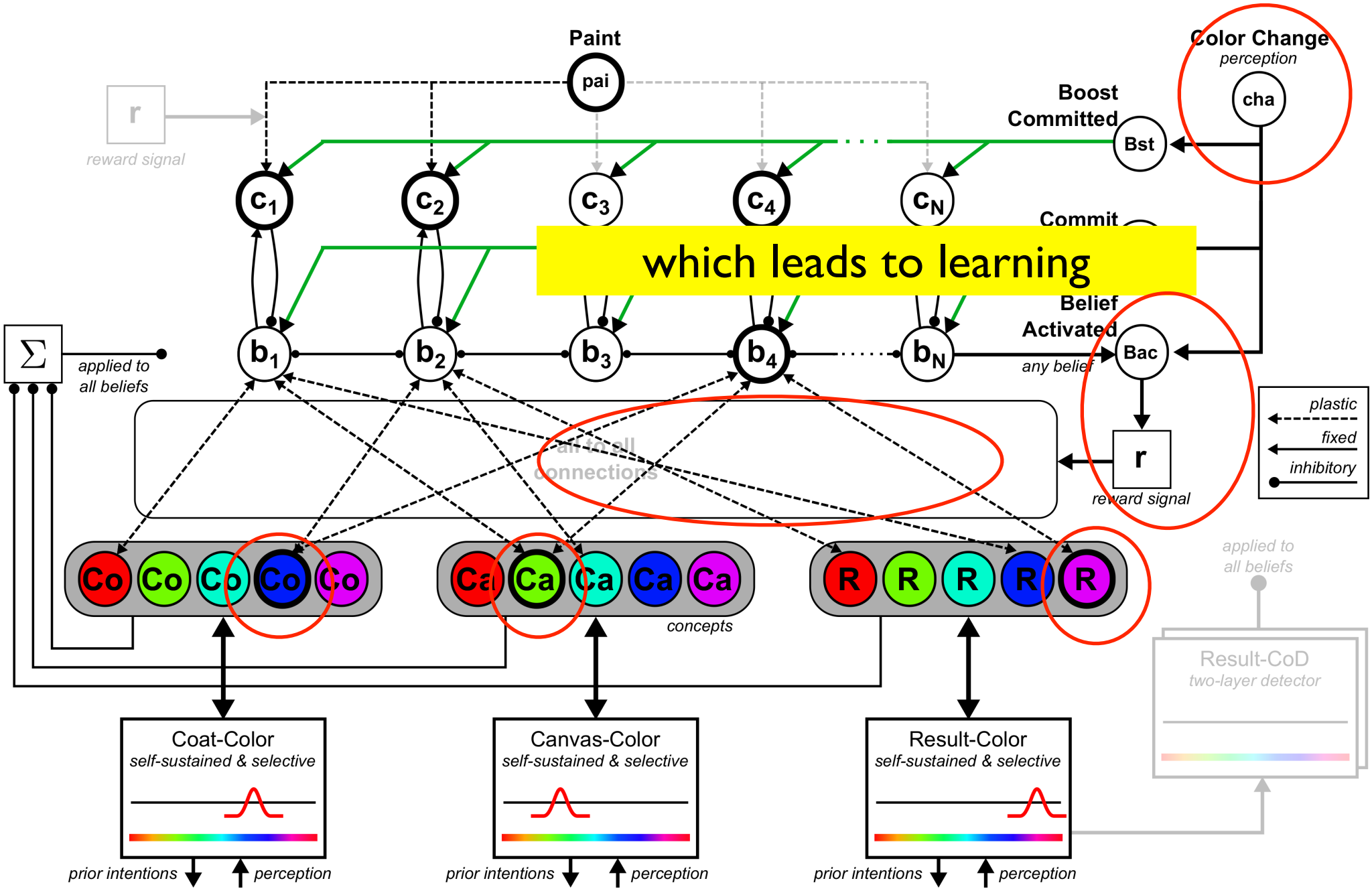
Commit nodes activated, task active



Commit nodes activated, task active



Commit nodes activated, task active



Autonomous learning

- act while aiming to learn (~task)
- recognize an opportunity for learning (~reward)
- map current experience to prior experience to update learning
- capacity to activation learned patterns ~ nodes ~enables that activation

Conclusion

- DFT is absolutely open to learning…
- in fact, it's strength is access to autonomous learning!
- most "NN learning" is not autonomous (and not learning)
- autonomous learning is hard and yet poorly understood